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Title: Artificial Neural Network Based Modeling of SSME Sensor Signals

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Introduction:

Recent SSME condition monitoring activities have focused on both real-time safety monitoring and post-test diagnostics. The current SSME safety system employs basic redline limits on critical parameters. Ignition confirm criteria are employed during start-up.. Advanced safety algorithms are being implemented using a large number of performance measurements. In order to prevent shutdowns or other controller actions due to sensor failures, a real-time sensor validation system is critical. Current SSME post-test data validation procedures are based on manual review of test data by experts. Techniques are being developed to automate the post-test diagnostic procedure. Part of an automated post-test diagnostic system would involve screening of the performance data and indicating any sensor failures. In addition, it is important to distinguish between a sensor failure and an engine fault. The long term goal of this research is to develop an artificial neural network based fault detection system which successfully identifies and differentiates between engine and sensor failures.

The objective of the current research is to develop and evaluate artificial neural network (ANN) based signal approximation models for use in SSME sensor validation. In order to develop SSME sensor signal approximation model, a set of sensor signals must be selected for use as input to each ANN model. Based on the set of input parameters, the neural network provides an estimate of the sensor signal being modeled. The sensor signal approximation models could be used for sensor fault detection and isolation during ground test firings. Further, such a signal approximation model would provide an estimate of a critical sensor signal which could be used for continued monitoring and analysis in the event of a sensor failure. If accurate and reliable models are available, future engines can continue to operate using a synthesized signal. This is especially attractive for space engines where the entire engine is anticipated to be a LRU (Line Replaceable Unit). The predicted signals can also be used to enhance post-test diagnostic evaluations and life prediction calculations

Background

As stated above, it is critical to identify erroneous sensor data. Erroneous sensor data may result from hard failures which are typically large in magnitude and occur rapidly (such as sudden open or short circuit conditions), or soft failures which are typically small and occur slowly with time (such as drift). A number of advanced statistical and expert system based techniques have been investigated to study their potential applicability to SSME sensor data validation and analysis [1-2]. It has been shown that neural networks can be used to approximate any continuous function [3-4]. Neural networks are well suited for problems in which the exact relationships between inputs and outputs are complex or unknown [3,5]. These conclusions may be applied to modeling of dynamical systems if the system state is sufficiently represented by the inputs of the neural network. Recently, the ability of artificial neural networks to model redlined sensor variables has been demonstrated [6,7]. The proposed research seeks to develop neural network based models of sensor variables which can be used for sensor validation, and engine fault detection and isolation.

Method and Approach

In this reserach project, artificial neural network based SSME parameter models for sensor validation are being developed. In a neural network based SSME sensor-signal model, a set of selected sensor signals is used as input. Based on input parameters, the neural network provides an estimate of the sensor-signal being modeled. The proposed sensor validation is based on analytical redundancy such that an analysis of errors between the actual and predicted values provides information about the sensor and/or engine health. Such a system could be helpful in characterizing sensor failures. It is expected that such analytical redundancy information could be useful in developing advanced engine safety algorithms. The proposed sensor validation system could be used for sensor fault detection and isolation during ground test firings. Further, such a system would provide an estimate of a critical sensor signal which could be used for continued monitoring and analysis in the event of a sensor failure.

To model a system function for a complex dynamical system such as the SSME, the choice of input parameters is crucial. Many approaches for input selection have been used or suggested. These include the use of characteristic equations, engine schematic analysis, correlation between candidate input parameters and the parameter to be modeled, and expert advice [2]. There are several constraints that complicate the task of selection of inputs to a SSME sensor- parameter model. The instrumentation on the SSME is extensive but incomplete. Therefore, it is possible that the available instrumentation may not completely describe any subsystem function being modeled. This makes the use of characteristic equations and correlation analysis difficult in input selection. Using understanding of engine schematics and behavior is very subjective and does not lead to a systematic method of input selection. In addition, it is not practical to use a large number of inputs in a model because of computational complexity and long processing times. This consideration is particularly important if the model is to be used for real-time analysis. In addition, in cases where the input data may be noisy, use of unnecessary inputs may affect the performance of the model. Thus, in our approach of modeling redlined sensor variables through neural networks, it is crucial to select an optimal or near-optimal set of input parameters through a systematic analysis. We used Genetic Algorithms to select inputs for a neural network based SSME sensor model [10-11, 14].

The generalization capability of a neural network based function approximator depends on the training. A single test firing provides more than 12,000 patterns. For better generalization, patterns from multiple test firings are required for training. This results in excessive training times. To reduce the time involved in training the ANN models, LVQ method was used to compress SSME ground test firing data [15]. The backpropagation network suffers from lack of reproducibility in results because of the dependence on initial weights and sub-optimal architecture. In addition, it may not provide a clear indication of network validity for creating signatures under the fault conditions. RBFNN is based on the radial basis function based representation of the input data which can be achieved through clustering. This architecture was implemented to develop SSME sensor model for PID # 233 for start-up duration [16].

Summary Of The Report

The objective of this proposal is to develop and evaluate artificial neural network (ANN) based signal approximation models for use in Space Shuttle Main Engine (SSME) sensor validation. In order to develop SSME sensor signal approximation model, a set of sensor signals must be selected for use as input to each ANN model. Based on the set of input parameters, the neural network provides an estimate of the sensor signal being modeled. The sensor signal approximation models could be used for sensor fault detection and isolation during ground test firings. Further, such a signal approximation model would provide an estimate of a critical sensor signal which could be used for continued monitoring and analysis in the event of a sensor failure.

Multi-layer Perceptron based feedforward networks with backpropagation learning have been used to model two redlined SSME sensor signals. During the last six months of NASA funding, Radial Basis Function Neural Network (RBFNN) architecture was used to develop SSME sensor models for start-up duration. In addition, backpropagation neural network based models were trained using the full SSME test firing data as well as reduced set of training vectors which were compressed using the Learning Vector Quantization (LVQ) method. New modifications to the Genetic Algorithm were made to automatically select an optimal set of input parameters for use in neural network based sensor models. The performance of backpropagation networks trained with full and reduced data, and RBFNN based models were evaluated and compared in nominal as well as simulated input sensor failure conditions. Three research papers and four technical reports were written based on the work accomplished in last six months. Three research papers were submitted to IEEE and AIAA journals for publication.

In the previous funding period, we identified three major areas of research work to be conducted. The accomplishments of the last funding period with a brief description of the proposed research in these areas are given below.

(1) A neural network based sensor model should be provided with a reasonably optimal set of input parameters. At present, the choice of this parameter set is highly dependent on an overall understanding of the engine. We proposed to use Genetic Algorithms (GA) to find an optimal or near-optimal set of input parameters, for each critical sensor signal to be modeled. We made new modifications to the Genetic Algorithm for use in SSME sensor modeling application. The optimal set of input parameters for PID # 233 (HPOT Discharge Temperature) was computed and used in developing backpropagation neural network based model for start-up duration. The performance of this model was compared with the backpropagation network using the input parameters selected by three experts. The network using the input parameters selected by GA performed better than the network using the parameter list selected by the experts. We propose to use the list of input parameters selected by experts as the starting solution in GA based optimization search. This will ensure that if there is a better solution possible, GA would be able to generate it.

(2) The generalization capability of a neural network based function approximator depends on the training. A single test firing provides more than 12,000 patterns. For better generalization, patterns from multiple test firings are required for training. This results in excessive training times. To reduce the time involved in training the ANN models, LVQ method was used to compress SSME ground test firing data. The backpropagation networks were trained for PID # 233 model for start-up duration with full as well as compressed data. The performance of these networks were compared. It was observed that clustering concept as implemented by LVQ method did not introduce significant errors up to a compression ration of 4:1. These results encouraged us to use a different neural network architecture called as Radial Basis Function Neural Network.

(3) The backpropagation network suffers from lack of reproducibility in results because of the dependence on initial weights and sub-optimal architecture. In addition, it may not provide a clear indication of network validity for creating signatures under the fault conditions. RBFNN is based on the radial basis function based representation of the input data which can be achieved through clustering. This architecture was implemented to develop SSME sensor model for PID # 233 for start-up duration. It was observed that the RBFNN architecture was more robust and less dependent on the variation in implementation such as number of clusters. By observing the position of a new input vector with respect to clusters or radial basis function representation, the network validity could be computed. In addition, the data reduction can be directly achieved through the clustering method with the merger of clusters with fewer number of vectors. This process reduces the complexity of the network without significantly affecting the performance.

For future work, we propose to further develop the network validity methods for RBFNN architecture. We will develop additional SSME sensor models using RBFNN for start-up duration and test their validity under the nominal operation and simulated input sensor failure conditions. To test the generalization capability of the network, RBFNN based models will be trained with larger number of test firings and their performance will be compared.

Results

New Genetic Algorithms were developed and implemented to address the optimal search in a noisy environment. These algorithms were used to select the input sensors for use in the ANN model of PID#233 , a redline parameter. Several selection and fitness evaluation methods were investigated to find the best performance of Genetic Algorithms. It was observed that validation based fitness evaluation with ranking selection method performed best in order to generate the input parameters list which provided least error in neural models. A conference paper was presented at the IEEE International Conference on Neural Networks [11]. Another paper was submitted to IEEE Transactions on Aerospace and Electronic Systems [14].

The LVQ topology was implemented to reduce the data for start-up operation on the selected ground test firings. In this investigation, the issue of reducing the training time of a feedforward neural network with backpropagation was addressed To improve training efficiency, the Quickprop learning algorithm was used to train the network on a reduced data set. The data reduction was obtained using the LVQ algorithm Various compression ratios were investigated to compress the training data The impact of various compression ratios on training was analyzed through the comparison of error statistics on the validation data In addition, the performance of the neural models was compared in simulated input sensor failure conditions. All neural models were trained to estimate PID 233, HPOT discharge temperature, during the start-up period of SSME ground test-firings A comparison of compression errors shows that the LVQ algorithm was able to compress the data set without introducing significant errors in the neural network model based estimation [15].

The Radial Basis Function neural network (RBFNN) with adaptive cluster variance was implemented to model PID#233 during the start-up operation. The performance of the RBFNN model was compared with the performance of feedforward neural network trained with Quickprop for the nominal as well as simulated sensor failure conditions. The RBFNN was not sensitive to choices in the number of units or neighborhood size as long as these choices were within a reasonable range. The feedforward neural network trained with Quickprop was sensitive to choices in architecture, learning rate, and weight initialization. The RBFNN had good generalization capability and provided good estimates of the HPOT discharge temperature despite widely varying behavior of the data. Equivalent performance was provided by both the nearest input vectors and by the p-nearest centroids based variance designs [16]. The RBFNN was able to train and recall faster than the Quickprop network. This difference in times will only increase as both the clustering algorithm and the weight finding procedure for the RBFNN are further optimized. In the hard failure input sensor condition, the RBFNN produced a faulted output. This is desirable so that the magnitude of the difference between the predicted and actual value of PID 233 will be indicative of a fault. It is then possible to use the clusters associated with the RBFNN to determine the fault locality. For the linear drift input failure condition, adequate generalization was provided to produce a valid output within a small time interval from the occurrence of the fault. After this time interval, the network produced an invalid output. This demonstrates that when a sensor value drifts but is not critically faulted, a valid output will still be generated by the network [15].

Conclusions and Future Plans

Radial Basis Function neural network architecture was implemented for PID#233 model. Its performance was compared with other architectures in nominal and simulated input sensor failure conditions. We are currently clustering the ground test firing data to characterize each test firing. Based on this characterization, corresponding neural network model will be trained and tested. Model for other PIDs during both start-up and mainstage operations will be developed. Use of these models in the sensor validation system being developed at the Aerojet is being explored.

One of the advantages of RBFNN architecture is that it is based on the radial basis function representation which is derived from the clusters of data vectors. If the minimum distance of an input vector is within any cluster variance, the network output is very reliable. In some cases when the clusters are of small variance, a new input vector may fall between them. The network may still interpolate and provide good output. The reliability in such cases will depend on how close the input vector is from the variance boundary of the nearest cluster. The network validity can thus be computed from the Euclidean distance of the input vector to the nearest cluster center normalized by the variance of the cluster. A fault in the input sensor can be characterized by the signatures indicating the time-based history of these flags. We propose to further develop and investigate the behavior of the network validity index and its use in characterization of input sensor failure.

The PI has discussed the use of neural models with Timothy Bickmore of Aerojet and Claudia Meyer of NASA LeRC. The ongoing work for sensor failure and characterization using RBF neural models is being investigated in coordination with Timothy Bickmore and Claudia Meyer.

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